Effects of Air Emissions Externalities on Optimal Ride-Hailing Fleet Electrification and Operations

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Ride-hailing is transforming transportation

- Transportation is now the largest source of U.S. GHGs
 - Primarily from passenger cars¹

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- Ride-hailing services by transportation network companies (TNCs) like Uber & Lyft are rapidly changing the passenger car landscape
 - Share of passenger trips in for-hire vehicles doubled in last decade²
 - 15% of intra-urban trips in San Francisco were served by Uber and Lyft (2016)
- Electrification: IPCC states passenger transportation must be electrified by 2035-2050 to limit warming to 1.5C³

1: US EPA, Office of Atmospheric Programs (2017). Inventory of U.S. greenhouse gas emissions and sinks, 1990-2016. 2: Conway, M., Salon, D., & King, D. (2018). Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. Urban Science, 2(3), 79. 3: Intergovernmental Panel on Climate Change: Global Warming of 1.5 °C: An IPCC special report. (2018) Cover slide image: Fleet Carma: "Electric Taxis Are On Their Way". <www.fleetcarma.com/electric-taxis-on-their-way/>

Electrify ride-hailing fleets?

Pros of Electric Vehicles (EVs)

Lower variable costs of fuel/energy Potential to reduce emissions

Natural fit for urban driving

Limitations of EVs

Higher fixed cost

Vehicles recharging can't serve trips

Recharging adds empty vehicle miles

Research questions

- 1. What technology mix is optimal for ride-hailing fleets?
- 2. How does internalizing externalities change optimal ride-hailing fleets?
- 3. How do location and model assumptions affect these results?



Background

Data & Methods

Results Summary

Approach

Supply-side

- Find optimal mix of vehicle technologies (conventional, hybrid, and battery electric) and operations to minimize cost
- Study how result changes under Pigovian tax, location, and alternative assumptions

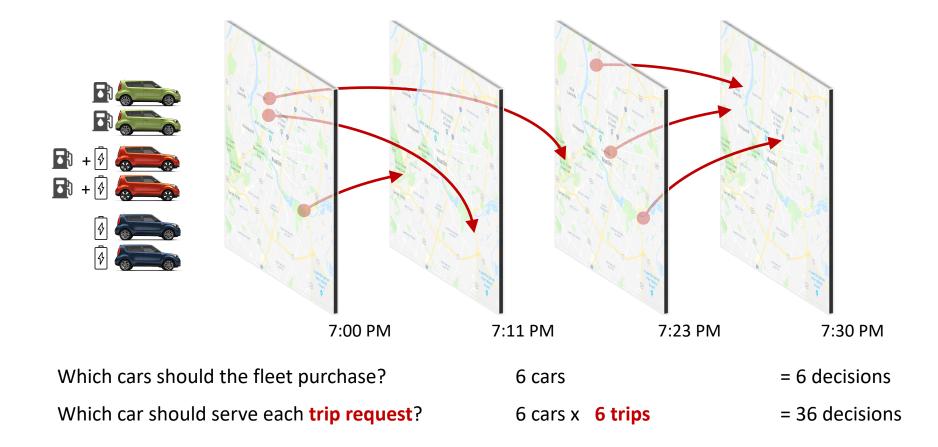
Demand side

- Exogeneous based on past trip data. Must be satisfied.
- Ideally would be equilibrium with demand elasticities, but difficult to credibly (and tractably) model substitution traveler mode choice and trip shedding in response to pricing
- More later

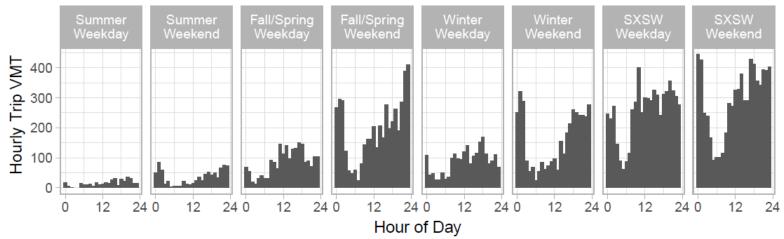
A network of arcs models fleet investment and dispatch



A network of arcs models fleet investment and dispatch



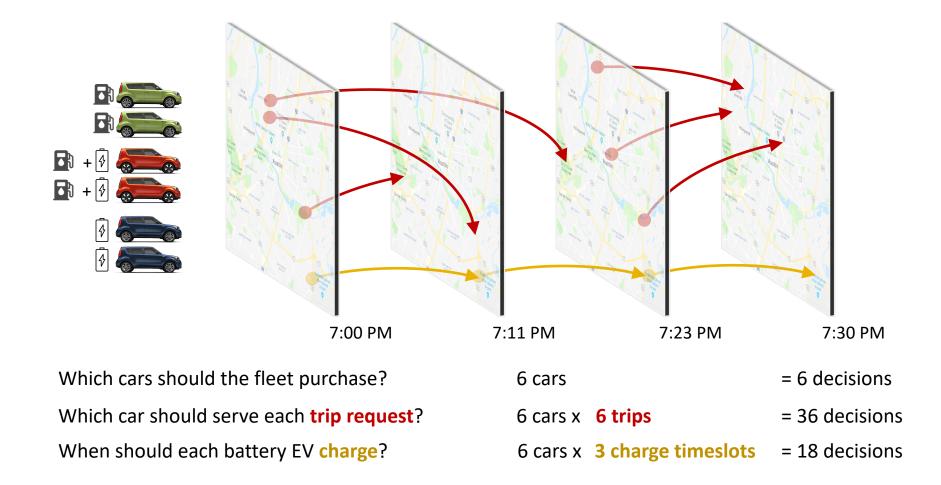
We use a sample of ride-hailing trips from RideAustin and modify cost inputs for Austin, LA, and NYC



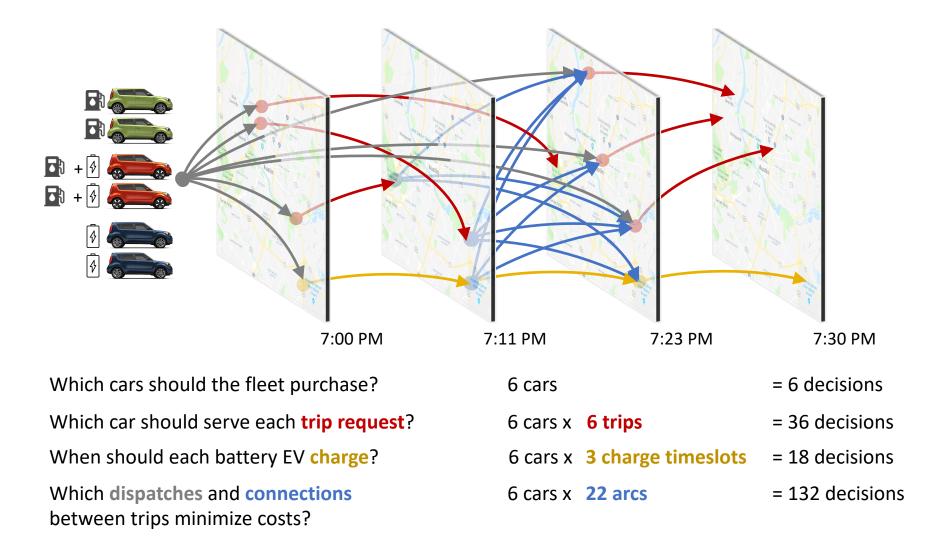
Hourly In-Sample Trip VMT

- RideAustin operated as a near-monopoly when Uber/Lyft left Austin
- We sample 5,000 representative RideAustin trips out of 1.5 million total
- To model Los Angeles and NYC, we change:
 - Electricity and gasoline prices
 - eGrid subregion of marginal emission factors
 - Counties of oil refinery and tailpipe emissions damages

A network of arcs models fleet investment and dispatch

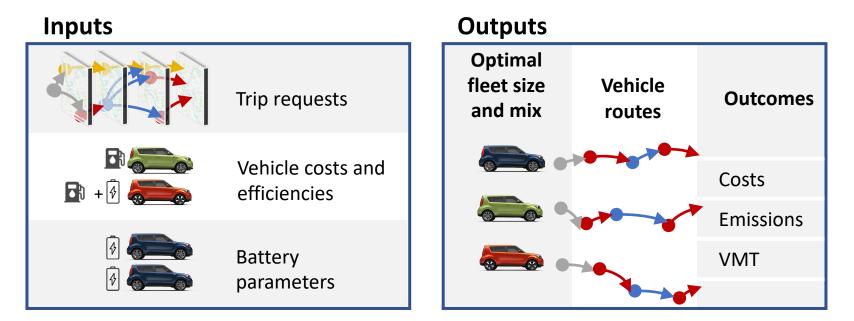


A network of arcs models fleet investment and dispatch



Model summary

Find fleet technology mix and operations to minimize cost (capital, energy, maintenance, externalities) subject to satisfying exogeneous trip demand



Compare results with and without a Pigovian tax on air emission externalities (SCC, APEEP3, InMAP, EASIUR)***

*other externalities unaffected by technology change;

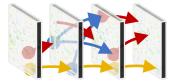
**supply chain treated as though Pigovian tax is passed through

Mixed-integer linear programming optimizes fleet investments and dispatch

Vehicles $k \in K$



Network L (source *r* to sink *s*)



- Arcs (*i*,*j*) from node *i* to *j*
- Demand $d_{i,j}$
- Variable cost $v_{k,i,j}$
- Energy change $e_{k,i,j}$
- Electricity price g_t at time t

Decisions X

- Assignments *a*_{k,i,j}
- Vehicle charge $I_{k,t}$ at time t
- Charger usage $c_{k,t}$
- # of purchases p_k for car k
- Annualized distance d_k
- Annualized capital costs h_k

Objective

$$\operatorname{minimize}_{\mathcal{X}} \sum_{k \in \mathcal{K}} h_k + \sum_{(i,j) \in \mathcal{A}} a_{k,i,j} v_{k,i,j} + \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_+} c_{k,t} g_t$$

Minimize costs of capital, energy and maintenance

Constraints (1/2)

$$\sum_{i \in \mathcal{V}} a_{k,i,j} = \sum_{i \in \mathcal{V}} a_{k,j,i} \quad \forall k \in K, j \in \mathcal{V} \setminus \{r, s\} \quad \text{Network flow conservation}$$
$$\sum_{k \in \mathcal{K}} a_{k,i,j} = n_{i,j} \quad \forall (i,j) \in \{\mathcal{A} : n_{i,j} > 0\} \quad \text{Passenger demand is met}$$

$$\sum_{j \in \mathcal{V} \setminus r} a_{k,r,j} = p_k \qquad \forall k \in \mathcal{K}$$

$$\sum_{(i,j)\in\mathcal{A}} m_{i,j} = d_k \qquad \forall k \in \mathcal{K}$$

$$\begin{aligned} h_k &\geq p_k \gamma_k & \forall k \in \mathcal{K} \\ h_k &\geq p_k \delta_{1,k} + d_k \zeta_{1,k} & \forall k \in \mathcal{K} \\ h_k &\geq p_k \delta_{2,k} + d_k \zeta_{2,k} & \forall k \in \mathcal{K}_B \end{aligned}$$

Vehicles must be purchased in order to be used

Each vehicle's usage is tracked

Each vehicle's capital cost increases with usage

Mixed-integer linear programming optimizes fleet investments and dispatch

Vehicles $k \in K$



Network L (source r to sink s)



- Arcs (*i*,*j*) from node *i* to *j*
- Demand *d*_{*i*,*j*}
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- Annualized capital costs h_k

Objective

 l_k

 $0 < l_{k,t} < b_k$

 $a_{k,i,j} \in \{0,1\}, p_k \in \{0,1\}$

 $\underset{\mathcal{X}}{\text{minimize}} \sum_{k \in \mathcal{K}} h_k + \sum_{(i,j) \in \mathcal{A}} a_{k,i,j} v_{k,i,j} + \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_+} c_{k,t} g_t$

Constraints (2/2)

$$c_{k,t} = l_{k,t+1} - l_{k,t} + \sum_{(i,j)\in\{\mathcal{A}:t_i=t,e_{k,i,j}<0\}} a_{k,i,j}e_{k,i,j} \ \forall k \in \mathcal{K}_B, t \in \mathcal{T}_A$$

$$l_{k,t+1} \leq l_{k,t} + \sum_{(i,j)\in\{\mathcal{A}:t_i=t\}} a_{k,i,j}e_{k,i,j} \qquad \forall k \in \mathcal{K}_B, t \in \mathcal{T}_+$$

 $a_{k,i,j} \in \mathbb{Z}_+, \ p_k \in \mathbb{Z}_+ \qquad \forall k \in \mathcal{K} \setminus \mathcal{K}_B, (i,j) \in \mathcal{A}$

$$l_{t+1} = l_{k,t} + \sum_{(i,j)\in\{\mathcal{A}:t_i=t\}} a_{k,i,j} e_{k,i,j} \quad \forall k \in \mathcal{K}_B, t \in \mathcal{T} \setminus \mathcal{T}_+$$

 $\forall k \in \mathcal{K}_B, (i, j) \in \mathcal{A}$

(timesteps with a charge timeslot)

Minimize costs of capital,

energy and maintenance

Charger usage is calculated

Charge level rises/falls

 $orall k \in \mathcal{K}_B, t \in \mathcal{T}$ Charge level is bounded by battery capacity

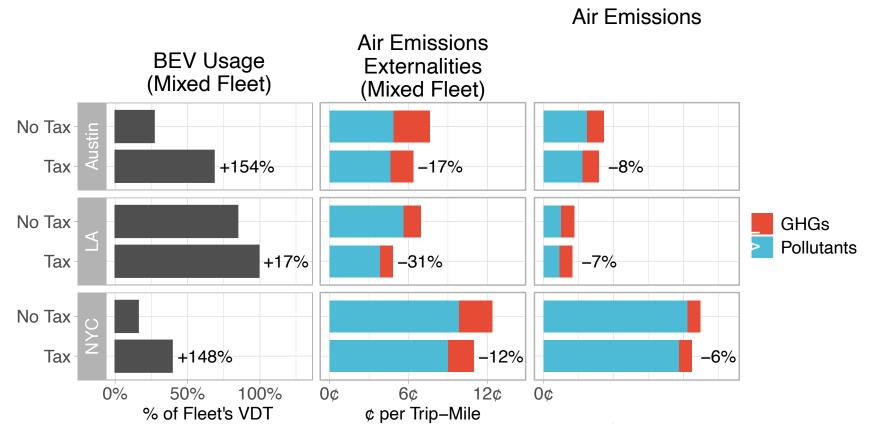
Purchases and assignments are integral

Background Data & Methods Results

Summary

Pigovian Tax on Air Emission Externalities \rightarrow

- greater electrification
- cleaner charge timing
- lower emissions



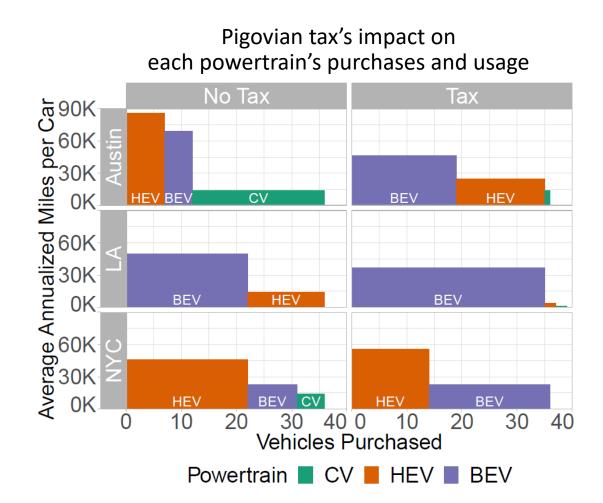
In present-day scenarios, taxing emissions always increases electrification, but the size of the shift varies widely

Austin, TX:

- A status-quo fleet purchases a majority of CVs and uses each HEV most heavily
- When taxed, the fleet purchases a majority of BEVs and uses them most heavily

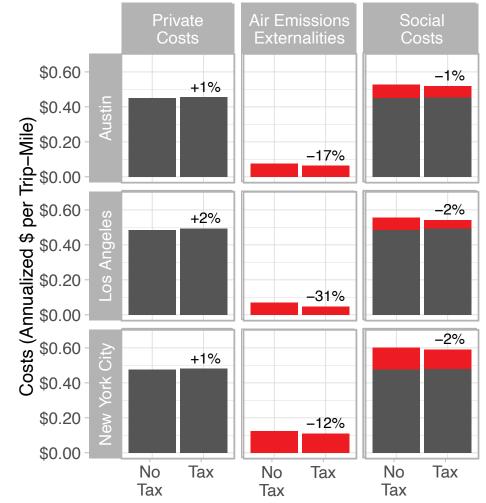
Los Angeles: a tax increases an alreadylarge degree of electrification

NYC: a tax increases HEV usage and BEV purchases while eliminating CVs



Emissions externalities can be reduced by 12-31% while increasing private costs 1-2%

- Across cities, imposing a Pigovian tax has little impact (1-2%) on the private costs of purchasing and operating the fleet
- The tax reduces health and climate change externalities by 12-31%, depending on city
 - ~\$30M/yr in LA
- The net efficiency gain (social costs) is small, but the effect on air emission externalities is significant



Sensitivity analysis

Key results robust across sensitivity scenarios; magnitude varies

- Externality valuation assumptions
 - Air pollution, GHGs
- Discount rate
- Labor costs
- Resale salvage value assumptions
- Vehicle cost, battery capacity
- Homogeneous fleets

Background Data & Methods Results

Summary

Summary

Pigovian tax on air emission externalities results in

- Increased vehicle electrification (17%-154%)
- Reduced air emission externalities (12%-31%)
- Small change in social welfare, but significant effect on air emission externalities - ~\$30M/yr in LA

Suggests a role for policy. However, blunt instruments favoring one technology over another may not be desirable

- Socially optimal fleet is a mix of technologies
- Socially optimal fleet varies by location and other factors that change over time

In context

We model a central decision-maker minimizing cost with perfect information of exogeneous demand

- Ignores market mechanisms (pricing, competition)
- Might approximate Uber/Lyft to the extent that...
 - TNCs lease vehicles to drivers for TNC driving
 - drivers respond to incentives about when to drive
 - good demand forecasting
 - fleet-wide regulation induces coordination (CA Clean Miles Standard)
- Likely better approximation of a future autonomous fleet
- Perfect information may overestimate ability to optimally schedule BEVs in particular



In context

We apply a life cycle Pigovian tax to the TNC

- In practice, supply chain would adjust
- Market power: pass-through to consumers would shift demand to other modes
- We ignore dual use
 - Overestimates the cost-saving potential of conventional vehicles for peak demand (but mitigated by salvage value)

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